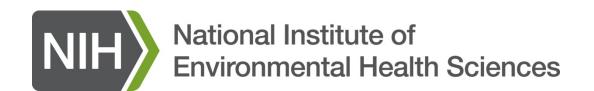
Biostatistics I - Introduction to Statistics and Experimental Design

Grace E. Kissling, Ph.D. Biostatistics Branch





Outline

· Last time:

- Study design
- Levels of measurement
- Numerical and graphical summaries
- Sample size determination

· Today:

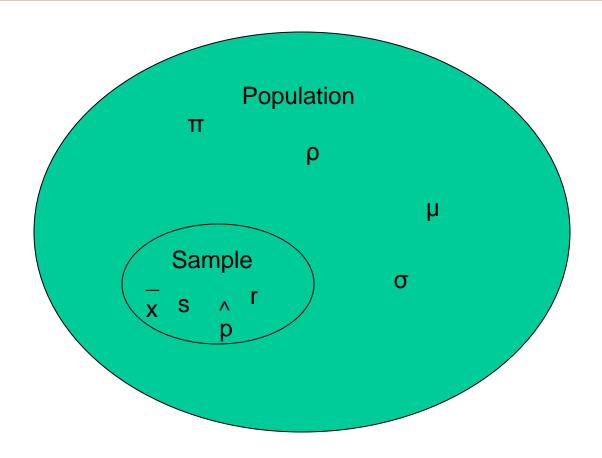
- Estimation
- Confidence intervals
- Principles of hypothesis testing

Estimation

A point estimate gives a single value, such as a mean.

Interval estimation gives a range of likely values.

Population vs. Sample

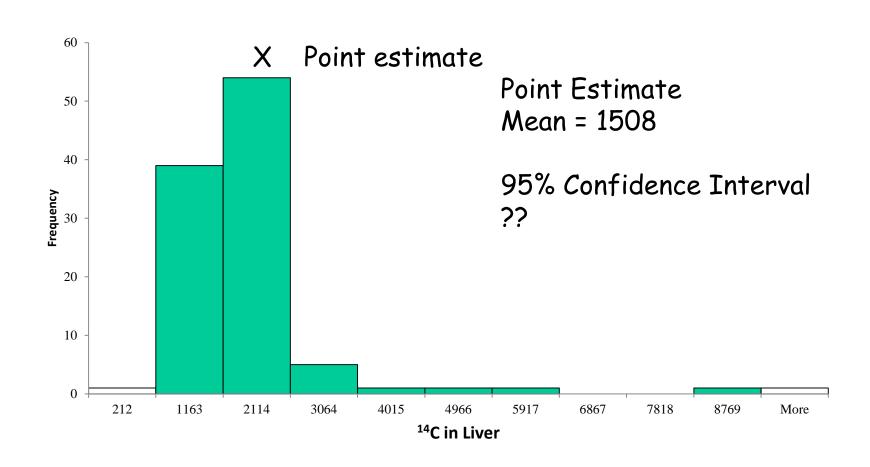


Confidence Intervals

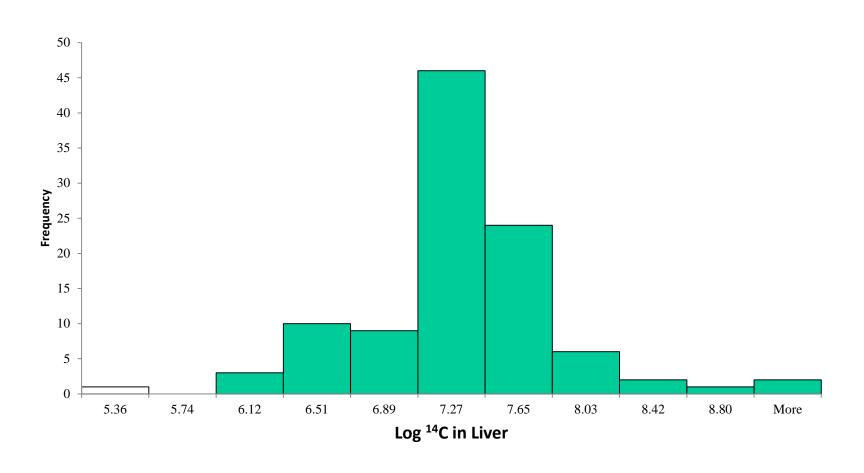
A 95% confidence interval for the mean gives an interval that has 95% probability of capturing the mean of the population

.... meaning that if we were to conduct the experiment an infinite number of times, 95% of the time, the confidence interval that we construct will include the mean of the population.

Example: Mean of Liver ¹⁴C



Example: Log(Liver ¹⁴C)



Confidence Intervals (CI)

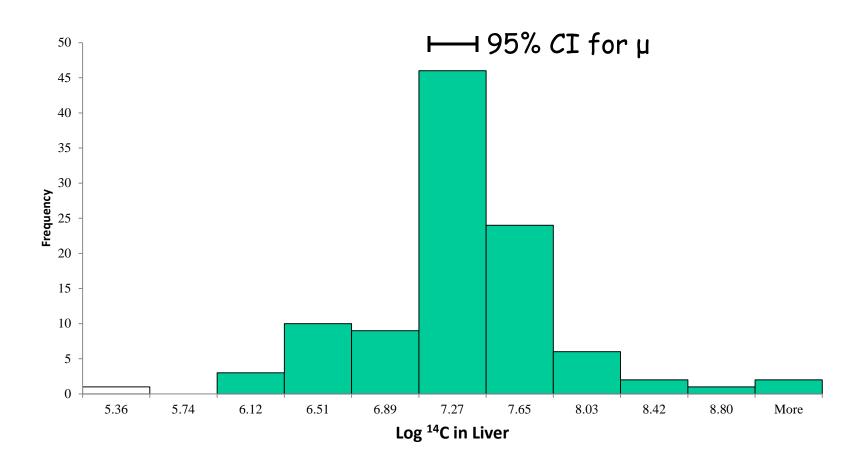
- For $log(^{14}C \text{ in liver})$, Mean = 7.14, S.D. = 0.56, N = 104
- The 95% CI for mean log(14C in liver) is

$$\bar{x} \pm t_{103..975} \times s.e.m. =$$

$$7.14 \pm 1.98 \times 0.56 / \sqrt{104}$$

(7.03, 7.25)

Example: Log(Liver ¹⁴C)



Confidence Intervals

- For $log(^{14}C \text{ in liver})$, Mean = 7.14, S.D. = 0.56, N = 104
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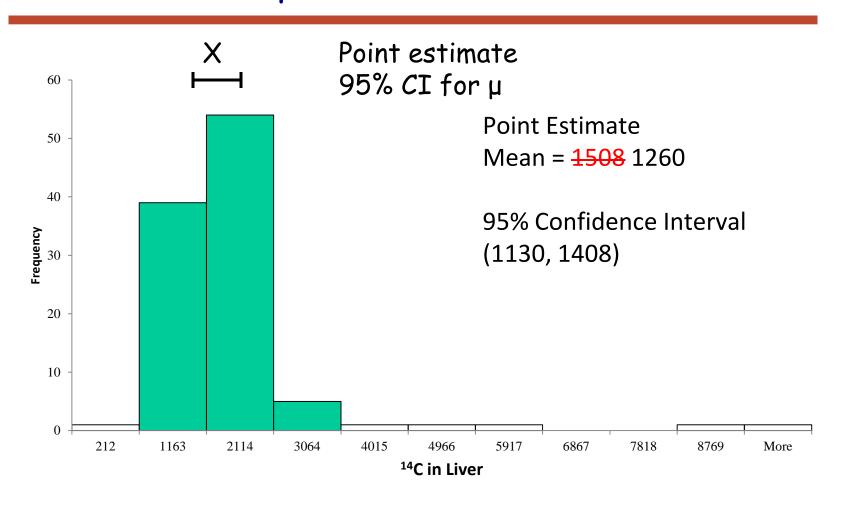
$$7.14 \pm 1.98 \times 0.56 / \sqrt{104}$$

$$(7.03,7.25)$$

Exponentiated, the 95% CI for mean ^{14}C in liver is (1130, 1408)

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Example: Mean of Liver ¹⁴C

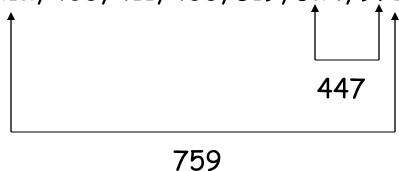


Outliers

- Unusual values that require examination
- <u>Do not</u> automatically discard outliers
- Several methods exist for detecting outliers
 - Massey-Dixon test or Dixon's Q test
 - Grubbs' test
 - Exceeds 3 standard deviations from the mean
 - Exceeds 1.5 IQRs from 25th or 75th percentiles

Outliers

- Example: ¹⁴C in liver (n = 7), Dixon's Q test
- 212, 403, 411, 433, 519, 524, 971



- Q = 447/759 = 0.59, look up in a Dixon's Q table to see if it exceeds the listed critical values
- For n = 7, the critical values are:
 - -0.507 at p = 0.10
 - 0.568 at p = 0.05 _____ 0.59, outlier!
 - -0.680 at p = 0.01

Outliers: Should I remove them?

- Legitimate reasons for removal:
 - Equipment malfunction
 - Impossible value
 - Error in data collection
 - Other mistake in the experiment
- Do not remove if:
 - An unusual value simply can't be explained
 - My data would "look better" if I removed it

Hypothesis Testing

- Null hypothesis
- Alternative hypothesis
- Test statistic
- · P-value
- · Conclusion

Hypotheses

- Null hypothesis, H₀
 - No difference, No effect, or No relationship
 - Always test Ho
 - \cdot assume H_0 true until there is sufficient evidence to the contrary
- Alternative hypothesis, H₁ or H_a
 - Usually, this is the research question

Test Statistic

- This is the evidence in favor of H₀
- Common test statistics have one of 4 well-known distributions:
 - Normal or z
 - Student's t
 - F
 - Chi-square

P-value

- P = Probability of the observed result or results more extreme, assuming H_0 is true
- One-sided or Two-sided P-value?
 - Can you predict a priori how groups will differ?
 - YES use one-sided p
 - NO use two-sided p

Conclusion

- If p is large, H_0 is supported.
- If p is small, H_0 is not supported, so we conclude that H_a is more likely correct.

 We typically use 0.05 to describe what is "large" (p > 0.05) and what is "small" (p < 0.05).

Keep in Mind....

- Our decision regarding H_0 is based on probabilities, so it could be incorrect.
- 0.05 is arbitrary.
- We use the significance level and the power to keep the probabilities of an incorrect decision low.

 H_0 is TRUE H_0 is FALSE

H₀ is TRUE

H₀ is FALSE

Reject Ho

Accept H₀

H₀ is TRUE

H₀ is FALSE

Reject Ho

Accept H₀

Type I error, False positive a	

Ho is TRUE

H₀ is FALSE

Reject Ho

Accept Ho

Type I error, False positive a

Correct decision

Ho is TRUE

 H_0 is FALSE

Reject Ho

Type I error, False positive a Correct decision $(1 - \beta)$, Power

Accept Ho

Correct decision

H₀ is TRUE

H₀ is FALSE

Reject H ₀	Type I error, False positive a	Correct decision (1 - β), Power
Accept H ₀	Correct decision	Type II error, False negative ß

Hypothesis Testing: Examples

Two-sample t-test

Paired t-test

Chi-square test

Fisher's exact test

Tests for normality

Hypothesis Testing: Mouse Body Weights

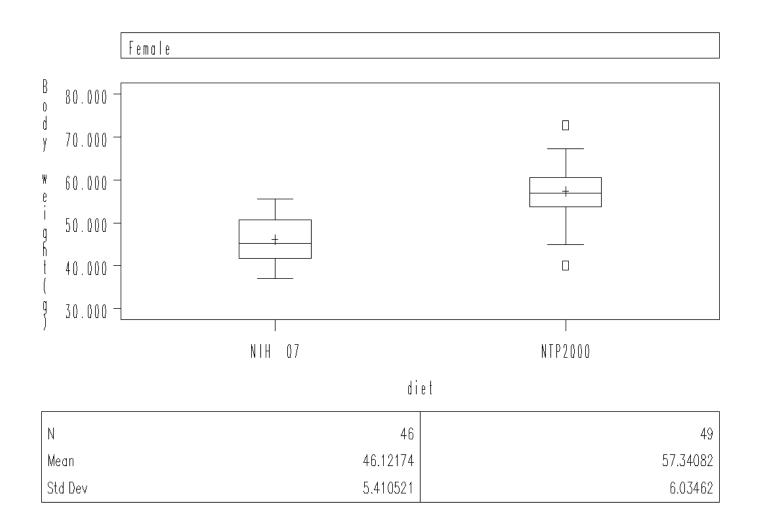
Body weights of 46 female mice on the NIH-07 diet and 49 female mice on the NTP 2000 diet were measured at one year of age.

Is there a <u>difference</u> in mean body weights between the two diet groups?

Two-sided p-value

Hypotheses

- H₀: Mean body weights are the same for the NIH-07 and NTP 2000 diet groups
- H_a: Mean body weights differ between the NIH-07 and NTP 2000 diet groups



Test Statistic and P-value

- NIH-07 Mean = 46.1q, SD = 5.4q, N = 46
- NTP 2000 Mean = 57.3q, SD = 6.0q, N = 49

Body weights are typically normally distributed

- Use a two-sample t-test
- t(93) = 9.42, p < 0.0001 (two-sided)

Conclusion

- If diet has no effect on one-year body weights, the probability of getting a mean difference of 11.2 g or more between the two diets is less than 0.0001.
- Because p is small (p < 0.0001), reject H_0 in favor of H_a
- Conclude that there is evidence that mean body weights of female mice at one year differ between the NIH-07 and NTP 2000 diet groups.

Selecting an Appropriate Test

The test statistic depends on:

- Study design
- Hypotheses
- Level of measurement of data (nominal, ordinal, interval/ratio)
- Shape of the distribution

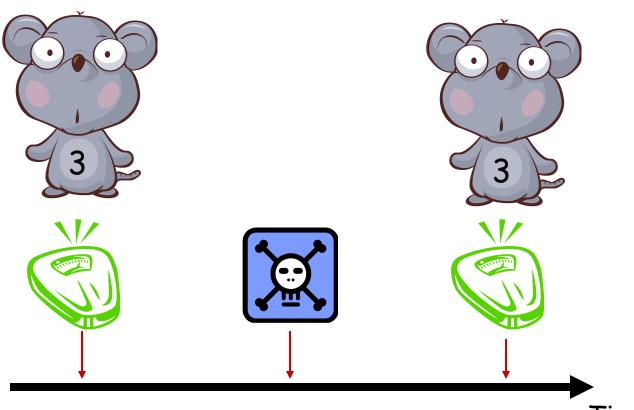
A New Study of Body Weights

• H_0 : Mean body weights are not affected by treatment with Compound X

 H_a: Mean body weights are <u>decreased</u> after treatment with Compound X

One-sided p-value

Experimental Design



The Data

Mouse	Before X	After X	Difference,
			After - Before
1	36.3	35.0	-1.3
2	43.5	42.2	-1.3
3	32.0	32.6	0.6
4	50.4	50.6	0.2
5	52.1	51.5	0.6
6	56.3	54.2	-2.1
7	52.4	50.8	-1.6
Mean	46.1	45.3	-0.9
S.D.	9.1	8.7	1.0

Test Statistic and P-value

- Before: Mean = 46.1, SD = 9.1, N = 7
- After: Mean = 45.3, SD = 8.7, N = 7

Body weights are typically normally distributed

- Use a paired t-test
- t(6) = 2.35, p = 0.029 (one-sided)

Conclusion

- Assuming that Compound X has no effect on body weights, the probability of getting an average decrease of 0.9 g or more after administering Compound X is 0.029.
- Because p is small (p = 0.029), reject H_0 in favor of H_a
- Conclude that there is evidence that mean body weights of mice are lower after exposure to Compound X than they were before exposure.

What if I had ignored the study design?

- Before: Mean = 46.1, SD = 9.1, N = 7
- After: Mean = 45.3, SD = 8.7, N = 7

Body weights are typically normally distributed

- Use a two-sample t test (ignores the pairing)
 t(12) = 0.18 p= 0.429, Not Significant

Hypothesis Testing: Chi-square Test

 H_0 : Tumor rates are the same in Control and Treated animals H_a : Tumor rates differ in Control and Treated animals

	Tumor	No Tumor	Total
Control	3	47	50
Treated	10	40	50
Total	13	87	100

 χ^2 =4.33 with 1 degree of freedom (df)

P = 0.037

Reject H₀ because 0.037 < 0.05. Conclude that there is a significant difference in tumor rates between Control and Treated animals.

Hypothesis Testing: Fisher's Exact Test

 H_0 : Tumor rates are the same in Control and Treated animals H_a : Tumor rates are higher in Treated than Control animals

P = Probability of the <u>observed data</u> or data <u>more extreme</u>, if H_0 is true

	Tumor	No Tumor
Control	3	47
Treated	10	40

	Tumor	No Tumor
Control	1	49
Treated	12	38

	Tumor	No Tumor
Control	2	48
Treated	11	39

	Tumor	No Tumor
Control	0	50
Treated	13	37 ₄₁

Hypothesis Testing: Fisher's Exact Test

	Tumor	No Tumor
Control	3	47
Treated	10	40

Prob = 0.0283

	Tumor	No Tumor
Control	1	49
Treated	12	38

Prob = 0.0009

	Tumor	No Tumor
Control	2	48
Treated	11	39

Prob = 0.0064

	Tumor	No Tumor
Control	0	50
Treated	13	37

Prob = 0.00005

Hypothesis Testing: Fisher's Exact Test

$$p = 0.0357$$
 (one-sided)

Because p = 0.0357 < 0.05, reject H_0 in favor of H_a that the tumor rate is higher in Treated animals than in Control animals.

	Tumor	No Tumor	
Control	3	47	50
Treated	10	40	50
	13	87	100

$$Prob = \frac{\binom{50}{3}\binom{50}{10}}{\binom{100}{13}} = 0.0283$$

	Tumor	No Tumor	
Control	2	48	50
Treated	11	39	50
	13	87	100

$$Prob = \frac{\binom{50}{2}\binom{50}{11}}{\binom{100}{13}} = 0.0064$$

	Tumor	No Tumor	
Control	1	49	50
Treated	12	38	50
	13	87	100

$$Prob = \frac{\binom{50}{1}\binom{50}{12}}{\binom{100}{13}} = 0.0009$$

	Tumor	No Tumor	
Control	0	50	50
Treated	13	37	50
•	13	87	100

$$Prob = \frac{\binom{50}{0} \binom{50}{13}}{\binom{100}{13}} = 0.00005$$

P-value = 0.0283 + 0.0064 + 0.0009 + 0.00005 = <math>0.0357

Hypothesis Testing: Test for Normality

Are my data normally distributed?

 H_0 : The data are normally distributed.

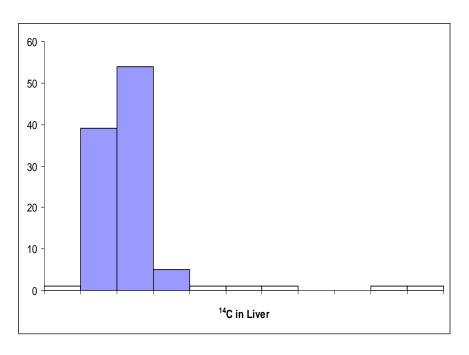
Ha: The data are not normally distributed.

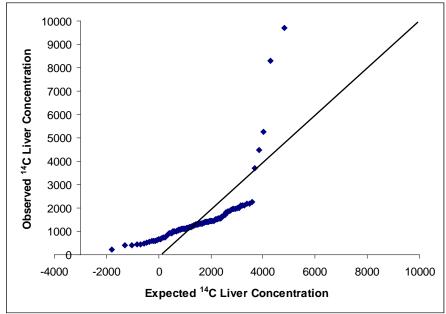
There are many tests for normality

- ·Shapiro-Wilks test
- Kolmogorov-Smirnov test
- ·Liliefors test
- ·Cramer-von Mises test
- ·Anderson-Darling test

Computation is tedious, so we rely on software to do the work.

Test for Normality: Recall ¹⁴C in Liver





Hypothesis Testing: Test for Normality

Are my data normally distributed?

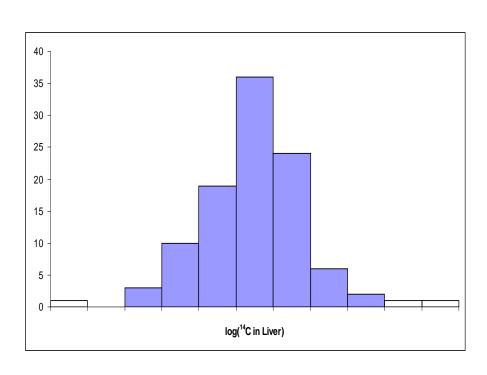
 H_0 : The data are normally distributed.

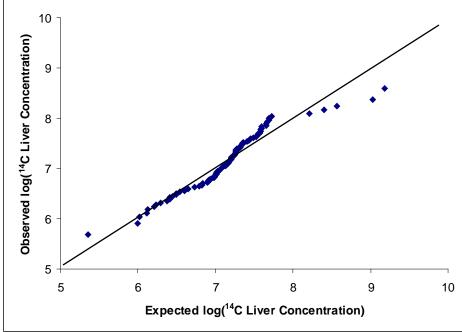
H_a: The data are not normally distributed.

14C in liver:
 Shapiro-Wilks statistic = 0.54 (using software)
 P < 0.0001

Reject H_0 : the data are not normally distributed.

Test for Normality: Recall log(14C in Liver)





Hypothesis Testing: Test for Normality

Are my data normally distributed?

 H_0 : The data are normally distributed.

H_a: The data are not normally distributed.

Log(^{14}C in liver): Shapiro-Wilks statistic = 0.98 P = 0.44

Accept H_0 : the data are normally distributed.

End of Biostatistics I

While I have presented some methods for analyzing data, one must be careful in applying them.

In Biostatistics II, we will take a look at some of the caveats.

"IF you torture the data long enough, it will confess. But there is no guarantee that it will tell you the truth."

-- from Berk, Regression Analysis: A Constructive Critique, 2004.